Title:

Subtitle

May 27, 2024

Abstract

1 Introduction

The National Institute of Standards and Technology Artificial Intelligence (AI) Risk Management Framework (RMF).[18]

2 Generative AI Incidents

3 Generative AI Governance

4 Generative AI Inventories

5 Generative AI Risk Tiers

6 Generative AI Risk Measurement

7 Generative AI Risk Management

Conclusion

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Abbreviations

- AI: Artificial Intelligence
- AI RMF: Artificial Intelligence Risk Management Framework
- GAI: Generative AI
- RMF: Risk Management Framework

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Appendix A: Example Generative AI–Trustworthy Characteristic Crosswalk

A.1: Trustworthy Characteristic to Generative AI Risk Crosswalk

Table A.1: Trustworthy Characteristic to Generative AI Risk Crosswalk.

Accountable and Transparent	Explainable and Interpretable	Fair with Harmful Bias Managed	Privacy Enhanced
Data Privacy Environmental Human-AI Configuration Information Integrity Intellectual Property Value Chain and Component Integration	Human-AI Configuration Value Chain and Component Integration	Confabulation Environmental Human-AI Configuration Intellectual Property Obscene, Degrading, and/or Abusive Content Toxicity, Bias, and Homogenization Value Chain and Component Integration	Data Privacy Human-AI Configuration Information Security Intellectual Property Value Chain and Component Integration

Safe	Secure and Resilient	Valid and Reliable
CBRN Information Confabulation Dangerous or Violent Recommendations Data Privacy Environmental Human-AI Configuration Information Integrity Information Security Obscene, Degrading, and/or Abusive Content Value Chain and Component Integration	Dangerous or Violent Recommendations Data Privacy Human-AI Configuration Information Security Value Chain and Component Integration	Confabulation Human-AI Configuration Information Integrity Information Security Toxicity, Bias, and Homogenization Value Chain and Component Integration

A.2: Generative AI Risk to Trustworthy Characteristic Crosswalk

Table A.2: Generative AI Risk to Trustworthy Characteristic Crosswalk.

CBRN Information	Confabulation	Dangerous or Violent Recommendations	Data Privacy
Safe	Fair with Harmful Bias Managed Safe Valid and Reliable	Safe Secure and Resilient	Accountable and Transparent Privacy Enhanced Safe Secure and Resilient

Environmental	Human-AI Configuration	Information Integrity	Information Security
Accountable and Transparent Fair with Harmful Bias Managed Safe	Accountable and Transparent Explainable and Interpretable Fair with Harmful Bias Managed Privacy Enhanced Safe Secure and Resilient Valid and Reliable	Accountable and Transparent Safe Valid and Reliable	Privacy Enhanced Safe Secure and Resilient Valid and Reliable

Intellectual Property	Obscene, Degrading, and/or Abusive Content	Toxicity, Bias, and Homogenization	Value Chain and Component Integration
Accountable and Transparent Fair with Harmful Bias Managed Privacy Enhanced	Fair with Harmful Bias Managed Safe	Fair with Harmful Bias Managed Valid and Reliable	Accountable and Transparent Explainable and Interpretable Fair with Harmful Bias Managed Privacy Enhanced Safe Secure and Resilient Valid and Reliable

Appendix B: Example Risk-tiering Materials for Generative AI

B.1: Example Adverse Impacts

Table B.1: Example adverse impacts, adapted from NIST 800-30r1 Table H-2 [17].

Level	Description

Harm to Operations	• Inability to perform current missions/business functions.
	  – In a sufficiently timely manner.
	  – With sufficient confidence and/or correctness.
	  – Within planned resource constraints.
	• Inability, or limited ability, to perform missions/business functions in the future.
	  – Inability to restore missions/business functions.
	  – In a sufficiently timely manner.
	  – With sufficient confidence and/or correctness.
	  – Within planned resource constraints.
	• Harms (e.g., financial costs, sanctions) due to noncompliance.
	  – With applicable laws or regulations.
	  – With contractual requirements or other requirements in other binding agreements (e.g., liability).
	• Direct financial costs.
	• Reputational harms.
	  – Damage to trust relationships.
	  – Damage to image or reputation (and hence future or potential trust relationships).

Harm to Assets	• Damage to or loss of physical facilities. • Damage to or loss of information systems or networks. • Damage to or loss of information technology or equipment. • Damage to or loss of component parts or supplies. • Damage to or of loss of information assets. • Loss of intellectual property.
Harm to Individuals	• Injury or loss of life. • Physical or psychological mistreatment. • Identity theft. • Loss of personally identifiable information. • Damage to image or reputation. • Infringement of intellectual property rights. • Financial harm or loss of income.

Harm to Other Organizations	• Harms (e.g., financial costs, sanctions) due to noncompliance.
	  – With applicable laws or regulations.
	  – With contractual requirements or other requirements in other binding agreements (e.g., liability).
	• Direct financial costs.
	• Reputational harms.
	  – Damage to trust relationships.
	  – Damage to image or reputation (and hence future or potential trust relationships).

Harm to the Nation	• Damage to or incapacitation of critical infrastructure.
	• Loss of government continuity of operations.
	• Reputational harms.
	  – Damage to trust relationships with other governments or with nongovernmental entities.
	  – Damage to national reputation (and hence future or potential trust relationships).
	• Damage to current or future ability to achieve national objectives.
	  – Harm to national security.
	• Large-scale economic or workforce displacement.

B.2: Example Impact Descriptions

Table B.2: Example Impact level descriptions, adapted from NIST SP800-30r1 Appendix H, Table H-3 [17].

Qualitative Values	Semi-Quantitative Values		Description
Very High	96-100	10	An incident could be expected to have multiple severe or catastrophic adverse effects on organizational operations, organizational assets, individuals, other organizations, or the Nation.
High	80-95	8	An incident could be expected to have a severe or catastrophic adverse effect on organizational operations, organizational assets, individuals, other organizations, or the Nation. A severe or catastrophic adverse effect means that, for example, the incident might: (i) cause a severe degradation in or loss of mission capability to an extent and duration that the organization is not able to perform one or more of its primary functions; (ii) result in major damage to organizational assets; (iii) result in major financial loss; or (iv) result in severe or catastrophic harm to individuals involving loss of life or serious life-threatening injuries.
Moderate	21-79	5	An incident could be expected to have a serious adverse effect on organizational operations, organizational assets, individuals other organizations, or the Nation. A serious adverse effect means that, for example, the incident might: (i) cause a significant degradation in mission capability to an extent and duration that the organization is able to perform its primary functions, but the effectiveness of the functions is significantly reduced; (ii) result in significant damage to organizational assets; (iii) result in significant financial loss; or (iv) result in significant harm to individuals that does not involve loss of life or serious life-threatening injuries.
Low	5-20	2	An incident could be expected to have a limited adverse effect on organizational operations, organizational assets, individuals other organizations, or the Nation. A limited adverse effect means that, for example, the incident might: (i) cause a degradation in mission capability to an extent and duration that the organization is able to perform its primary functions, but the effectiveness of the functions is noticeably reduced; (ii) result in minor damage to organizational assets; (iii) result in minor financial loss; or (iv) result in minor harm to individuals.
Very Low	0-4	0	An incident could be expected to have a negligible adverse effect on organizational operations, organizational assets, individuals other organizations, or the Nation.

B.3: Example Likelihood Descriptions

Table B.3: Example likelihood levels, adapted from NIST SP800-30r1 Appendix G, Table G-3 [17].

Qualitative Values	Semi-Quantitative Values		Description
Very High	96-100	10	An incident is almost certain to occur; or occurs more than 100 times a year.
High	80-95	8	An incident is highly likely to occur; or occurs between 10-100 times a year.
Moderate	21-79	5	An incident is somewhat likely to occur; or occurs between 1-10 times a year.
Low	5-20	2	An incident is unlikely to occur; or occurs less than once a year, but more than once every 10 years.
Very Low	0-4	0	An incident is highly unlikely to occur; or occurs less than once every 10 years.

B.4: Example Risk Tiers

Table B.4: Example risk assessment matrix with 5 impact levels, 5 likelihood levels, and 5 risk tiers, adapted from NIST SP800-30r1 Appendix I, Table I-2 [17] .

Likelihood	**Level of Impact**				
	Very Low	**Low**	**Moderate**	**High**	**Very High**
Very High	Very Low (Tier 5)	Low (Tier 4)	Moderate (Tier 3)	High (Tier 2)	Very High (Tier 1)
High	Very Low (Tier 5)	Low (Tier 4)	Moderate (Tier 3)	High (Tier 2)	Very High (Tier 1)
Moderate	Very Low (Tier 5)	Low (Tier 4)	Moderate (Tier 3)	Moderate (Tier 3)	High (Tier 2)
Low	Very Low (Tier 5)	Low (Tier 4)	Low (Tier 4)	Low (Tier 4)	Moderate (Tier 3)
Very Low	Very Low (Tier 5)	Very Low (Tier 5)	Very Low (Tier 5)	Low (Tier 4)	Low (Tier 4)

B.5: Example Risk Descriptions

Table B.5: Example risk descriptions, adapted from NIST SP800-30r1 Appendix I, Table I-3 [17] .

Qualitative Values	Semi-Quantitative Values		Description
Very High	96-100	10	Very high risk means that an incident could be expected to have multiple severe or catastrophic adverse effects on organizational operations, organizational assets, individuals, other organizations, or the Nation.
High	80-95	8	High risk means that an incident could be expected to have a severe or catastrophic adverse effect on organizational operations, organizational assets, individuals, other organizations, or the Nation.
Moderate	21-79	5	Moderate risk means that an incident could be expected to have a serious adverse effect on organizational operations, organizational assets, individuals, other organizations, or the Nation.
Low	5-20	2	Low risk means that an incident could be expected to have a limited adverse effect on organizational operations, organizational assets, individuals, other organizations, or the Nation.
Very Low	0-4	0	Very low risk means that an incident could be expected to have a negligible adverse effect on organizational operations, organizational assets, individuals, other organizations, or the Nation.

B.6: Practical Risk-tiering Questions

B.6.1: Confabulation: How likely are system outputs to contain errors? What are the impacts if errors occur?

B.6.2: Dangerous and Violent Recommendations: How likely is the system to give dangerous or violent recommendations? What are the impacts if it does?

B.6.3: Data Privacy: How likely is someone to enter sensitive data into the system? What are the impacts if this occurs? Are standard data privacy controls applied to the system to mitigate potential adverse impacts?

B.6.4: Human-AI Configuration: How likely is someone to use the system incorrectly or abuse it? How likely is use for decision-making? What are the impacts of incorrect use or abuse? What are the impacts of invalid or unreliable decision-making?

B.6.5: Information Integrity: How likely is the system to generate deepfakes or mis or disinformation? At what scale? Are content provenance mechanisms applied to system outputs? What are the impacts of generating deepfakes or mis or disinformation? Without controls for content provenance?

B.6.6: Information Security: How likely are system resources to be breached or exfiltrated? How likely is the system to be used in the generation of phishing or malware content? What are the impacts in these cases? Are standard information security controls applied to the system to mitigate potential adverse impacts?

B.6.7: Intellectual Property: How likely are system outputs to contain other entities' intellectual property? What are the impacts if this occurs?

B.6.8: Toxicity, Bias, and Homogenization: How likely are system outputs to be biased, toxic, homogenizing or otherwise obscene? How likely are system outputs to be used as subsequent training inputs? What are the impacts of these scenarios? Are standard nondiscrimination controls applied to mitigate potential adverse impacts? Is the application accessible to all user groups? What are the impacts if the system is not accessible to all user groups?

B.6.9: Value Chain and Component Integration: Are contracts relating to the system reviewed for legal risks? Are standard acquisition/procurement controls applied to mitigate potential adverse impacts? Do vendors provide incident response with guaranteed response times? What are the impacts if these conditions are not met?

Appendix C: List of Selected Model Testing Suites ("Evals")

C.1: Selected Model Testing Suites Organized by Trustworthy Characteristic

Table C.1: Selected model testing suites organized by trustworthy characteristic.

Accountable and Transparent
An Evaluation on Large Language Model Outputs: Discourse and Memorization (see Appendix B)[4]
Big-bench: Truthfulness [24]
DecodingTrust: Machine Ethics [27]
Evaluation Harness: ETHICS [11]
HELM: Copyright [2]
Mark My Words [19]

Fair with Harmful Bias Managed
BELEBELE [1]
Big-bench: Low-resource language, Non-English, Translation
Big-bench: Social bias, Racial bias, Gender bias, Religious bias
Big-bench: Toxicity
DecodingTrust: Fairness
DecodingTrust: Stereotype Bias
DecodingTrust: Toxicity
C-Eval (Chinese evaluation suite) [13]
Evaluation Harness: CrowS-Pairs
Evaluation Harness: ToxiGen
Finding New Biases in Language Models with a Holistic Descriptor Dataset [23]
From Pretraining Data to Language Models to Downstream Tasks: Tracking the Trails of Political Biases Leading to Unfair NLP Models [9]
HELM: Bias
HELM: Toxicity
MT-bench [29]
The Self-Perception and Political Biases of ChatGPT [20]
Towards Measuring the Representation of Subjective Global Opinions in Language Models [7]

Privacy Enhanced
HELM: Copyright
llmprivacy [25]
mimir [6]

Safe
Big-bench: Convince Me
Big-bench: Truthfulness
HELM: Reiteration, Wedging
Mark My Words
MLCommons [26]
The WMDP Benchmark [15]

Table C.1: Selected model testing suites organized by trustworthy characteristic (continued).

Secure and Resilient
Catastrophic Jailbreak of Open-source LLMs via Exploiting Generation [12]
DecodingTrust: Adversarial Robustness, Robustness Against Adversarial Demonstrations
detect-pretrain-code [22]
In-The-Wild Jailbreak Prompts on LLMs [21]
JailbreakingLLMs [3]
llmprivacy
mimir
TAP: A Query-Efficient Method for Jailbreaking Black-Box LLMs [16]

Valid and Reliable
Big-bench: Algorithms, Logical reasoning, Implicit reasoning, Mathematics, Arithmetic, Algebra, Mathematical proof, Fallacy, Negation, Computer code, Probabilistic reasoning, Social reasoning, Analogical reasoning, Multi-step, Understanding the World
Big-bench: Analytic entailment, Formal fallacies and syllogisms with negation, Entailed polarity
Big-bench: Context Free Question Answering
Big-bench: Contextual question answering, Reading comprehension, Question generation
Big-bench: Morphology, Grammar, Syntax
Big-bench: Out-of-Distribution
Big-bench: Paraphrase
Big-bench: Sufficient information
Big-bench: Summarization
DecodingTrust: Out-of-Distribution Robustness, Adversarial Robustness, Robustness Against Adversarial Demonstrations
Eval Gauntlet: Reading comprehension [5]
Eval Gauntlet: Commonsense reasoning, Symbolic problem solving, Programming
Eval Gauntlet: Language Understanding
Eval Gauntlet: World Knowledge
Evaluation Harness: BLiMP
Evaluation Harness: CoQA, ARC
Evaluation Harness: GLUE
Evaluation Harness: HellaSwag, OpenBookQA, TruthfulQA
Evaluation Harness: MuTual
Evaluation Harness: PIQA, PROST, MC-TACO, MathQA, LogiQA, DROP
FLASK: Logical correctness, Logical robustness, Logical efficiency, Comprehension, Completeness [28]
FLASK: Readability, Conciseness, Insightfulness
HELM: Knowledge
HELM: Language
HELM: Text classification
HELM: Question answering
HELM: Reasoning
HELM: Robustness to contrast sets
HELM: Summarization
Hugging Face: Fill-mask, Text generation [8]
Hugging Face: Question answering
Hugging Face: Summarization
Hugging Face: Text classification, Token classification, Zero-shot classification
MASSIVE [10]
MT-bench

C.2: Selected Model Testing Suites Organized by Generative AI Risk

Table C.2: Selected model testing suites by organized generative AI risk.

CBRN Information
Big-bench: Convince Me
Big-bench: Truthfulness
HELM: Reiteration, Wedging
MLCommons
The WMDP Benchmark

Confabulation
BELEBELE
Big-bench: Algorithms, Logical reasoning, Implicit reasoning, Mathematics, Arithmetic, Algebra, Mathematical proof, Fallacy, Negation, Computer code, Probabilistic reasoning, Social reasoning, Analogical reasoning, Multi-step, Understanding the World
Big-bench: Analytic entailment, Formal fallacies and syllogisms with negation, Entailed polarity
Big-bench: Context Free Question Answering
Big-bench: Contextual question answering, Reading comprehension, Question generation
Big-bench: Convince Me
Big-bench: Low-resource language, Non-English, Translation
Big-bench: Morphology, Grammar, Syntax
Big-bench: Out-of-Distribution
Big-bench: Paraphrase
Big-bench: Sufficient information
Big-bench: Summarization
Big-bench: Truthfulness
C-Eval (Chinese evaluation suite)
DecodingTrust: Out-of-Distribution Robustness, Adversarial Robustness, Robustness Against Adversarial Demonstrations
Eval Gauntlet Reading comprehension
Eval Gauntlet: Commonsense reasoning, Symbolic problem solving, Programming
Eval Gauntlet: Language Understanding
Eval Gauntlet: World Knowledge
Evaluation Harness: BLiMP
Evaluation Harness: CoQA, ARC
Evaluation Harness: GLUE
Evaluation Harness: HellaSwag, OpenBookQA, TruthfulQA
Evaluation Harness: MuTual
Evaluation Harness: PIQA, PROST, MC-TACO, MathQA, LogiQA, DROP
FLASK: Logical correctness, Logical robustness, Logical efficiency, Comprehension, Completeness
FLASK: Readability, Conciseness, Insightfulness
Finding New Biases in Language Models with a Holistic Descriptor Dataset
HELM: Knowledge
HELM: Language
HELM: Language (Twitter AAE)
HELM: Question answering
HELM: Reasoning
HELM: Reiteration, Wedging
HELM: Robustness to contrast sets
HELM: Summarization
HELM: Text classification
Hugging Face: Fill-mask, Text generation
Hugging Face: Question answering
Hugging Face: Summarization
Hugging Face: Text classification, Token classification, Zero-shot classification
MASSIVE
MLCommons
MT-bench

Table C.2: Selected model testing suites by organized generative AI risk (continued).

Dangerous or Violent Recommendations
Big-bench: Convince Me
Big-bench: Toxicity
DecodingTrust: Adversarial Robustness, Robustness Against Adversarial Demonstrations
DecodingTrust: Machine Ethics
DecodingTrust: Toxicity
Evaluation Harness: ToxiGen
HELM: Reiteration, Wedging
HELM: Toxicity
MLCommons

Data Privacy
An Evaluation on Large Language Model Outputs: Discourse and Memorization (with human scoring, see Appendix B)
Catastrophic Jailbreak of Open-source LLMs via Exploiting Generation
DecodingTrust: Machine Ethics
Evaluation Harness: ETHICS
HELM: Copyright
In-The-Wild Jailbreak Prompts on LLMs
JailbreakingLLMs
MLCommons
Mark My Words
TAP: A Query-Efficient Method for Jailbreaking Black-Box LLMs
detect-pretrain-code
llmprivacy
mimir

Environmental
HELM: Efficiency

Information Integrity
Big-bench: Analytic entailment, Formal fallacies and syllogisms with negation, Entailed polarity
Big-bench: Convince Me
Big-bench: Paraphrase
Big-bench: Sufficient information
Big-bench: Summarization
Big-bench: Truthfulness
DecodingTrust: Machine Ethics
DecodingTrust: Out-of-Distribution Robustness, Adversarial Robustness, Robustness Against Adversarial Demonstrations
Eval Gauntlet: Language Understanding
Eval Gauntlet: World Knowledge
Evaluation Harness: CoQA, ARC
Evaluation Harness: ETHICS
Evaluation Harness: GLUE
Evaluation Harness: HellaSwag, OpenBookQA, TruthfulQA
Evaluation Harness: MuTual
Evaluation Harness: PIQA, PROST, MC-TACO, MathQA, LogiQA, DROP
FLASK: Logical correctness, Logical robustness, Logical efficiency, Comprehension, Completeness
FLASK: Readability, Conciseness, Insightfulness
HELM: Knowledge
HELM: Language
HELM: Question answering
HELM: Reasoning
HELM: Reiteration, Wedging
HELM: Robustness to contrast sets
HELM: Summarization
HELM: Text classification
Hugging Face: Fill-mask, Text generation
Hugging Face: Question answering
Hugging Face: Summarization
MLCommons
MT-bench
Mark My Words

Table C.2: Selected model testing suites by organized generative AI risk (continued).

Information Security
Big-bench: Convince Me
Big-bench: Out-of-Distribution
Catastrophic Jailbreak of Open-source LLMs via Exploiting Generation
DecodingTrust: Out-of-Distribution Robustness, Adversarial Robustness, Robustness Against Adversarial Demonstrations
Eval Gauntlet: Commonsense reasoning, Symbolic problem solving, Programming
HELM: Copyright
In-The-Wild Jailbreak Prompts on LLMs
JailbreakingLLMs
Mark My Words
TAP: A Query-Efficient Method for Jailbreaking Black-Box LLMs
detect-pretrain-code
llmprivacy
mimir

Intellectual Property
An Evaluation on Large Language Model Outputs: Discourse and Memorization (with human scoring, see Appendix B)
HELM: Copyright
Mark My Words
llmprivacy
mimir

Obscene, Degrading, and/or Abusive Content
Big-bench: Social bias, Racial bias, Gender bias, Religious bias
Big-bench: Toxicity
DecodingTrust: Fairness
DecodingTrust: Stereotype Bias
DecodingTrust: Toxicity
Evaluation Harness: CrowS-Pairs
Evaluation Harness: ToxiGen
HELM: Bias
HELM: Toxicity

Toxicity, Bias, and Homogenization
BELEBELE
Big-bench: Low-resource language, Non-English, Translation
Big-bench: Out-of-Distribution
Big-bench: Social bias, Racial bias, Gender bias, Religious bias
Big-bench: Toxicity
C-Eval (Chinese evaluation suite)
DecodingTrust: Fairness
DecodingTrust: Stereotype Bias
DecodingTrust: Toxicity
Eval Gauntlet: World Knowledge
Evaluation Harness: CrowS-Pairs
Evaluation Harness: ToxiGen
Finding New Biases in Language Models with a Holistic Descriptor Dataset
From Pretraining Data to Language Models to Downstream Tasks: Tracking the Trails of Political Biases Leading to Unfair NLP Models
HELM: Bias
HELM: Toxicity
The Self-Perception and Political Biases of ChatGPT
Towards Measuring the Representation of Subjective Global Opinions in Language Models

Appendix D: List of Common Adversarial Prompting Strategies

D.1: Common Adversarial Prompting Strategies by Trustworthy Characteristic

D.2: Common Adversarial Prompting Strategies by Generative AI Risk

Appendix E: Common Risk Controls for Generative AI

E.1: Common Risk Controls for Generative AI by Trustworthy Characteristic

E.2: Common Risk Controls for Generative AI by Generative AI Risk

Appendix F: Example Low-risk Generative AI Measurement and Management Plan

7.1 F.1: Example Low-risk Generative AI Measurement and Management Plan by Trustworthy Characteristic

7.2 F.2: Example Low-risk Generative AI Measurement and Management Plan by Generative AI Risk

Appendix G: Example Medium-risk Generative AI Measurement and Management Plan

7.3 G.1: Example Medium-risk Generative AI Measurement and Management Plan by Trustworthy Characteristic

7.4 G.2: Example Medium-risk Generative AI Measurement and Management Plan by Generative AI Risk

Appendix H: Example High-risk Generative AI Measurement and Management Plan

7.5 H.1: Example High-risk Generative AI Measurement and Management Plan by Trustworthy Characteristic

7.6 H.2: Example High-risk Generative AI Measurement and Management Plan by Generative AI Risk